Available online at www.sciencedirect.com
ScienceDirect
The Social Science Journal 46 (2009) 776–786
The SOCIAL SCIENCE JOURNAL
www.elsevier.com/locate/soscij

Elicitation of health values from mortality risk reduction

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Received 22 September 2008; received in revised form 21 April 2009; accepted 6 May 2009

Abstract

There are concerns regarding uncertainty about the accuracy of applying available empirical willingness-to-pay (WTP) estimates for reducing accidental deaths to value changes in risks of pollution-related deaths. In this study, we develop a theoretical model on defining WTP, and its determinants, and derive WTP estimates for changes in pollution-related mortality risks with varying morbidity and timing attributes. A survey is designed and conducted with 100 subjects. Each subject was to complete five choice sets and provided a range of implicit values of statistical life (VSL). The choices are estimated using the logit procedure. And, using the results of estimated multinomial logit model, the VSL is estimated to about $6.2 million.

Keywords: Willingness-to-pay; Mortality risk; Value of statistical life; Multinomial logit model

1. Introduction

Analysts have been exploring the dimensions of mortality risk that may be relevant to determining willingness-to-pay (WTP). Many studies have used either revealed preference (RP) or stated preference (SP) approaches to estimate average WTP (or WTA) for small changes in risks of accidental death. Literatures that discuss these applications include Fisher, Chestnut, and Violette (1989), Miller (1989), Cropper and Freeman (1991), Viscussi (1993), Viscussi, Hakes, and Carlin, 1997), Larson et al. (1999), Krupnick, Alberini, Cropper, and Simon (1999), and Krupnick, Cropper, Alberini, and Simon (2004). While the large number of SP studies would

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0362-3319/$ – see front matter
doi:10.1016/j.soscij.2009.05.003

appear to indicate that the methodology has matured, SP is still very much an evolving methodology and one for which there are significant methodological concerns, including sources of potential error and bias[1], the cognitive aspects of survey questions, and overall reliability of results. Even with these weaknesses, the SP methodology continues to evolve as critical public policy tools, especially in the areas of the environment and health (Dennis, 2007). The results from previous studies using SP methodologies are being used as the basis for the monetary valuation of mortality risk in assessments of the potential benefits of regulatory and policy decisions.

For the most part, available empirical WTP estimates for reducing mortality risks are for risks of accidental death, such as on-the-job or transportation accidents. Risks of accidental death usually involve an immediate relationship between cause and effect and little, if any, morbidity prior to death. Risks of accidental death are not very age dependent, staying at fairly constant rates relative to age. On the other hand, many pollution-related mortality risks are increasing with age. Also, some air pollution-related risks of premature death may fall disproportionately on the already ill segments of the exposed population, may involve substantial latencies between exposure and onset of a health effect, and may involve prolonged and painful illnesses preceding premature death. Because of these different attributes of the mortality risk, there is considerable uncertainty about the accuracy of applying available empirical WTP estimates for reducing accidental deaths to value changes in risks of pollution-related deaths.

One of the issues that has been raised about how WTP to reduce mortality risk may vary is that the value of reducing risk may be a function of the number of life-years at risk. Applying a single WTP for all mortality risks assumes that the value is invariant with the remaining life expectancy of the person at risk. Many analysts have noted that death is never entirely prevented; it is merely delayed to some degree or another. However, plausible it may seem that WTP to reduce mortality risk is related to the remaining life expectancy for those at risk, exactly how WTP to reduce mortality risk varies with the remaining life expectancy of the individual has not been determined empirically. Remaining life expectancy is, of course, closely related to age.

The question of how WTP to reduce mortality risk varies with the attributes of the risk cannot be addressed without taking into account the morbidity component of these health effects in addition to the risk of premature mortality. The purpose of this study is to develop a theoretical model on defining WTP, and its determinants, and derive WTP estimates for changes in pollution-related mortality risks with varying morbidity and timing attributes. The instrument used in this study is based on a stated preference approach designed to elicit subjects' preferences between alternative scenarios that involve varying mortality risks and attributes of these risks.

2. WTP estimation model

2.1. Choice model for attributes survey

In this section, a theoretical model is developed in an effort to focus on defining WTP, and its determinants, for reductions in risks of serious illnesses with a high probability of mortality.

This is being done to assist in the identification and specification of parameters relevant for the valuation of pollution-related morbidity and mortality risks. We have approached this as a utility maximization process for the individual consistent with random utility models and expected utility theory. Because this involves choices over time and choices with sequential probabilistic events, the model needs to incorporate nonlinearities, discounting and intertemporal choice, and conditional probabilities.

The model needs to account for individual and illness attributes such as:

1) *Characteristics of the individual:*
   - Socio-demographic (age; gender; ethnicity; household income; size of household).
   - Individual's personal health risks (personal health history; family health history).
2) *Characteristics of the health risk:*
   - Timing (time until onset of illness; time from onset until death or recovery).
   - Discomfort and impairment (level of discomfort during illness).
   - Probabilities (of being affected by the illness; of dying if affected).

Holding the utility *function* constant over time (and suppressing individual notation), utility is a function of consumption and health: $U(H_t,C_t)$ where the marginal utility of consumption increases as health improves: $\partial U^2/\partial C_t \partial H_t > 0$. The present value of remaining lifetime consumption (PVLC) (from t_n = time now to t_N = time of natural death without disease caused by air pollution) is $\mathrm{PVLC} = \int_{t_n}^{t_N} U(H_t, C_t)\mathrm{e}^{-\delta t}\,\mathrm{d}t$ where δ is the individual rate of time preference.

Modeling PVLC in terms of a single health risk defining ρ as the probability of remaining fully healthy, ϕ as the survival probability if sick, and H_t^i as the time path of health, where $i = H$ if never ill, $i = I$ if ill and then recover, and $i = D$ if ill and then die, the expected utility (EU) or expected PVLC is:

$$EU = \rho \underbrace{\int_{t_n}^{t_N} U(H_t^H, C_t)\mathrm{e}^{-\delta t}\ \mathrm{d}t}_{A} + (1-\rho)\phi \underbrace{\int_{t_n}^{t_N} U(H_t^I, C_t)\mathrm{e}^{-\delta t}\ \mathrm{d}t}_{B} + (1-\rho)(1-\phi)\underbrace{\int_{t_n}^{t_N} U(H_t^I, C_t)\mathrm{e}^{-\delta t}\ \mathrm{d}t}_{C} \qquad (1)$$

where Term A = utility if never ill; Term B = utility if ill and then recover; Term C = utility if ill and then die. Fig. 1 shows this conceptually where we are interested in measuring areas B and C, welfare losses from morbidity and mortality, respectively.

We further developed the model where the individual faces a discrete risk of getting ill sometime in the future due to current exposure. This model can be used to examine values for marginal changes in health risks based on model parameters to be estimated from the survey data. For instance, this model could be used to look at change in the probability of health ($\partial\rho$). Let t_0 be the time to onset of disease caused by air pollution; r the length of impairment prior

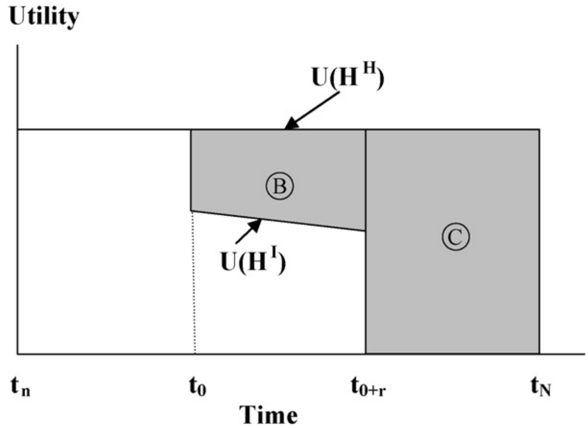

Fig. 1. Utility losses from air pollution health risks.

to recovery; t_{0+r} the time to death or recovery if ill:

$$\frac{\partial EU}{\partial \rho} = \underbrace{\int_{t_0}^{t_{0+r}} U(H_t^H, C_t) - U(H_t^I, C_t)\mathrm{e}^{-\delta t}\ \mathrm{d}t}_{A} + \underbrace{\int_{t_{0+r}}^{t_N} \phi U(H_t^r, C_t)\mathrm{e}^{-\delta t}\ \mathrm{d}t}_{B} \tag{2}$$

where Term A is the present value of the difference between being healthy and ill during potential illness and Term B is the present value of full health after recovery weighted by probability of not dying if ill, ϕ. The second term indicates part of the change in expected utility due to a change in the probability of getting ill is the probability weighted loss of utility if one dies.

Alternatively, the model can be used to look at the value of changes in the survival probability if sick (ϕ = probability of surviving if sick):

$$\frac{\partial EU}{\partial \phi} = (1-\rho)\int_{t_{0+r}}^{t_N} U(H_t^H, C_t)\mathrm{e}^{-\delta t}\ \mathrm{d}t \tag{3}$$

This is the value of a healthy life after recovery weighted by the probability of getting ill in the first place. The model would also be used to look at values/issues such as:

- Changes in time until illness onset ($\partial EU/\partial t_0$).
- Changes in the level of impairment during illness ($\partial EU/\partial H^I$).
- Changes in the length of impairment prior to recovery ($\partial EU/\partial r$).

Note that in expected utility (Eq. (1) above) if the probability of recovery if ill is nil ($\phi = 0$), ρ represents the probability of death. Furthermore, if the length of illness is extremely short ($r = 0$) the problem simplifies to the timing of onset of illness, t_0.

$$EU = \underbrace{\int_{t_n}^{t_0} U(H_t^H, C_t)\mathrm{e}^{-\delta t}\ \mathrm{d}t}_{A} + \underbrace{\rho\int_{t_0}^{t_N} U(H_t^H, C_t)\mathrm{e}^{-\delta t}\ \mathrm{d}t}_{B} \tag{4}$$

From this we can calculate the value of life as a function of time to onset of illness:

$$\frac{\partial EU}{\partial \rho} = \int_{t_0}^{t_N} U(H_t^H, C_t)\mathrm{e}^{-\delta t}\ \mathrm{d}t. \tag{5}$$

This is the total value of a healthy life from the time of onset until natural death. This suggests that we could use the model, setting r and ϕ to zero, to derive value of life estimates as a function of the probability of death similar to standard on-the-job value of statistical life (VSL) estimates.

2.2. Choice model for data analysis

The multinomial logit model is generally used to estimate models based on the type of choice experiment used. This choice experiment framework is consistent with the discrete choice random utility model, the same theoretical framework often used with contingent valuation method (CVM) and travel cost data (McFadden, 1974; Ben-Akiva & Lerman, 1985; Mitchell & Carson, 1989). Within this framework, we assume that individuals have preferences over any pair of good, for example, health alternatives, represented as a choice between living in one of two different cities. Individual i chooses the health alternative j that provides the greatest utility, U_{ij}, where alternative j is a member of the choice set of C possible alternatives. The probability that individual i will choose health alternative j over k is:

$$Pr_i\{j\,\text{over}\,k\} = Pr_i\{U_{ij} \geq U_{ik};\ j \neq k\} \tag{6}$$

The utility individual i receives from choosing health alternative j is:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{7}$$

where V_{ij} is assumed deterministic from both the researcher's and the individual's perspective, and ε_{ij} is random from the researcher's perspective, but known by the individual. Eq. (7) is the conditional indirect utility function and identifies maximum utility conditional on the choice of health alternative j. By substituting Eq. (7) into Eq. (6) and rearranging, the probability of choosing alternative j over alternative k becomes:

$$Pr_i\{j\,\text{over}\,k\} = Pr_i\{V_{ij} - V_{ik} \geq \varepsilon_{ik} - \varepsilon_{ij}; j \neq k\} \tag{8}$$

It is assumed that each ε_{ij} is independently drawn from a univariate Type I extreme value distribution (McFadden, 1974) with the cumulative distribution function:

$$F(\varepsilon_i) = \exp[-\mathrm{e}^{-r_i(\varepsilon_i - \alpha)}] \tag{9}$$

where α is a location parameter set equal to zero and r_i is a positive scale parameter. This distribution has a mode of α, mean of $\alpha + \gamma/r_i$, where γ is Euler's constant (~0.58), and variance $\sigma_\varepsilon^2 = \pi^2/6r_i^2$. We assume that the random components of the conditional indirect utility function, ε_{ij}, are independent and identically distributed across individuals and choice occasions; that is, $r_i = r\forall i$. Without loss of generality, r is set equal to 1. The probability that

Table 1
Attributes survey outline.

Section	Objectives
Cover page	(1) Increase interest in completing survey (2) Convey specific information (using illustrations) (3) Identify sponsor and provide contact information
Introduction	(1) Begin to obtain subject's own attitudes regarding health (2) Introduce concept of risk factors and pollution as a risk factor (3) Introduce the range of health risks that might be associated with pollution exposure
Effects on quality of life	(1) Introduce terminology on suffering and impairment
Timing	(1) Introduce concepts of length of time to onset and 1ength of illness (2) Presentation of timing information in choice sets
Probabilities	(1) Introduce health probability information (2) Educate respondents on compound probabilities (3) Presentation of probability information in choice sets
Comparing two illnesses	(1) Introduce description of an illness as a set of attributes, using the attributes already defined (2) Introduce concept of choices between illnesses
Choices between cities	(1) Introduce premise of the choice sets as a choice between two cities (2) Introduce cost of living change as another attribute
Choices sets	(1) Collect responses to choice sets (5 sets) (2) Collect information on strength of preference or other information to better mode1 and understand choices
Socio-demographics	(1) Obtain relevant socio-demographic information for modeling and for comparison to population

individual i will choose health alternative j over k becomes:

$$Pr_i\{j \text{ over } k\} = \frac{e^{V_{ij}}}{e^{V_{ij}} + e^{V_{ik}}} \quad \text{and} \quad \frac{Pr_i\{j \text{ over } k\}}{Pr_i\{j \text{ over } k\}} = \frac{e^{V_{ij}}}{e^{V_{ik}}} \tag{10}$$

3. The attributes survey

A survey was designed with the aim of estimating changes in pollution-related mortality risk with varying morbidity and timing attributes. The attribute survey was conducted in two rounds of focus groups, one set of one-on-one interviews, and two group sessions where subjects completed to questionnaire on their own followed by debriefing discussion. Table 1 provides an outline of the attributes survey and overall objectives of each section.

Health risk attributes are divided into three categories: effects on quality of life, timing of onset and length of illness, and probabilities of getting ill or dying. Attributes were selected to try to cover the range of illness that may reasonably be expected to be associated with pollution exposures. The description of each attributes are shown in Table 2.

A total of about 100 subjects participated in the survey. Each subject was to complete 5 choice sets, which would provide a total of 500 observations. Fourteen choice questions were

Table 2
Description of attribute levels for choice sets.

Attribute levels	Description
City	Different scenarios for two cities in the amount and type of pollution and cost of living
SET Q#	Choice set question number in the survey
IMPAIR	Discomfort or impairment level 0—none: normal good health, no discomfort or impairment 1—mild: mild amount of discomfort or impairment 2—moderate: some moderate discomfort or limitation in vigorous activities 3—significant: significant discomfort or limitation with work and leisure activities 4—severe: severe discomfort or limitation, confined to home or hospital, and need assistance caring for self
ONSET	Time to onset (in days)
LENGTH_ILL	Length of illness (in days)
PROB_GET	Probability of getting ill after exposure (in 10,000)
PROB_DIE	Probability of dying from the illness (in 10)
PROB_GET_DIE	Probability of getting ill and dying (in 100,000)
COST	Increase in the annual cost of living to live in this city (in $)

unanswered leaving a total of 486 observations (across 100 subjects). The attribute levels for the 5 choice sets are shown in Table 3. Subjects were presented numbers of years rather than numbers of days for the ONSET (time to onset) and LENGTH_ILL (length of illness) categories. These have been converted to days for data analysis.

4. Results

The choice sets were designed manually to offer choices that provided a range of implicit VSL in terms of the difference within each choice set. Other attributes were arbitrarily assigned. For the implementation of this instrument, choice sets need to be designed orthogonally in order to increase the likelihood of being able to estimate the model parameters. Multiple versions of the instrument will also be needed to allow more variation in the choice sets presented. For the choice sets there was significant correlation of the attribute levels which made parameter estimation more difficult. Table 4 shows the attribute correlation matrix.

The choices are estimated using the logit procedure because the model is essentially a logit model with pairwise choices. The data are analyzed using the PHREG procedure in SAS, which is the appropriate procedure for estimating multinomial logit models as developed above (Table 5).

The results indicate that PROB_GET_DIE and COST are significant and of the expected sign. For the marginal changes (increase) of the probability of getting ill and dying and the cost of living will have negative effect on the expected PVLC. Other coefficients are not significant probably because of the correlation of the attribute levels and small sample size. Although length of illness and time to onset is not significant, it has the expected signs. Longer the suffering of the illness and longer the time to onset will have a negative and a positive effect on the expected PVLC, respectively. Among the negative effect attributes levels, the probability of

Table 3
Attribute levels for choice sets.

Choice Set #	City	SET Q#	IMPAIR (category)	ONSET (days)	LENGTH_ILL (days)	PROB_GET (in 10,000)	PROB_DIE (in 10)	PROB_GET_DIE (in 100,000)	COST ($)
1	A	18	4	1	1	10	2	20	600
	B	18	2	3650	365	1	2	2	1500
2	C	22	2	3650	365	10	2	20	1500
	D	22	4	1	1	1	2	2	1000
3	E	23	4	1825	1825	5	1	5	600
	F	23	4	7300	1825	5	5	25	500
4	G	24	1	3650	1	10	2	20	1500
	H	24	1	7300	1	5	5	25	500
5	I	25	1	1	365	1	1	1	1000
	J	25	4	1	365	10	5	50	500

Table 4
Correlation matrix of attribute levels.

	IMPAIR	ONSET	LENGTH_ILL	PROB_GET	PROB_DIE	PROB_GET_DIE	COST
IMPAIR	1.00						
ONSET	−0.32	1.00					
LENGTH_ILL	0.45	0.29	1.00				
PROB_GET	0.11	0.00	−0.13	1.00			
PROB_DIE	0.15	0.54	0.08	0.23	1.00		
PROB_GET_DIE	0.20	0.16	−0.06	0.72	0.78	1.00	
COST	−0.54	−0.03	−0.37	−0.05	−0.54	−0.42	1.00

Table 5
Multinomial logit analysis of attribute survey.

Variables	Estimated coefficient	Wald Chi-square
IMPAIR	0.23837	0.3084
ONSET	0.00004	0.1309
LENGTH_ILL	−0.00117	0.2955
PROB_GET_DIE	−0.06620	9.1089
COST	−0.00107	3.7148

getting ill and dying is most effective on the expected PVLC with coefficient value of −0.066.

As discussed in the model section, this information can be used to derive a value of statistical life. Assuming time until onset is zero, length of illness is zero, and impairment is zero (which is irrelevant when length of illness is zero), the only relevant variables are probability of getting ill and then dying and the cost. This information represents the individual's tradeoff between the probability of dying now and cost, similar to accidental death VSL estimates.

Dividing the marginal utility of a 1 in 100,000 chance of getting ill and dying (PROB_GET_DIE) by the marginal utility of money (COST) and multiplying by 100,000 provides an estimate of the VSL: $(-0.06620/-0.00107) \times 100{,}000 = \$6{,}186{,}000$. Based on this analysis the value of life (all else constant) is about \$6.2 million, which is well within the normal estimates of the VSL from other studies.

5. Conclusion and future research

Most of available empirical WTP estimates are for risks of accidental death in circumstances where individuals are voluntarily exposed to risks (e.g., choosing a job or driving a car). Some potentially important differences exist between the contexts of these available estimates and the contexts of most environmental health risk changes being evaluated in a cost–benefit analysis. Environmental health risks are primarily related to illness rather than accidents. Deaths as a result of environmental pollution exposures may be fairly quick, such as with heart attack or pneumonia, or may involve prolonged illness, such as with cancers or chronic respiratory disease. With environmental risks, there may also be a substantial lag between the time of a change in exposure and the time that a noticeable change in health is realized, such as with cancers that may occur many years after a harmful exposure. All of these factors represent differences in the nature of the risk that could potentially result in a different WTP for an equivalent magnitude reduction in that risk.

Thus, in this study, we develop a WTP estimation model and designed a survey with the aim to estimate changes in pollution-related mortality risk with varying morbidity and timing attributes in order to explore the issues raised above. Through the model, the relevant parameters for valuation of pollution-related morbidity and mortality risks are identified. The model is then used to derive value of life estimates as a function of the probability of death. This approach stands in contrast to other approaches that directly estimating values for particular air pollutants and illnesses.

A total of about 100 subjects participated in the survey and their responded data are analyzed by multinomial logit models. The results indicated that the variable of the chance of getting ill and dying and the marginal utility of money showed significance and expected sign. The VSL is derived using the information of the estimated model, and it is estimated to about $6.2 million.

The estimated results in this study are based on a small sample. We have not explored more complex models with interactions between socio-demographic characteristics and choice attributes. Particularly, the budget constraint has not been integrated into the model appropriately. It will be useful to determine how to integrate the budget constraint as well as describing a payment vehicle in the survey and the time period over which payments would occur. The results in this study are encouraging though in terms of providing a reasonable estimate of the VSL and in terms of the significance and signs of several of the model parameters.

Note

1. Potential errors and bias of SP includes: (1) the tendency to overstate or understate WTP in order to affect policy (strategic bias); (2) when respondents are forced to evaluate goods/attributes for which they have little or no experience (information bias); (3) the tendency for reference points for bidding games and payment card mechanisms to induce higher or lower responses (starting point bias); (4) the tendency for hypothetical payments to differ from actual payments due to a difficulty in correctly picturing the situation (hypothetical bias).

Acknowledgement

This research was supported by the Korea Ministry of Environment as "The GAIA Project".

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